Offline Signature Recognition using Modular Neural Networks with Fuzzy Response Integration

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Abstract. This paper presents a new offline signature recognition system based on Modular Neural Networks (MNN) and fuzzy inference system. The proposed MNN consists of three different modules, each using different image features as input, these are: edge detection, curvelet transform, and the Hough transform. The Mamdani fuzzy inference system is then used to combine the outputs from each of these modules. The experimental results obtained by using a data base of 30 individuals' signatures show that the proposed modular architecture can achieve very high 96.6% recognition accuracy with a small test set of 60 images. Therefore, we can conclude that modular architectures and more specifically our proposed system can provide a suitable platform to build a signature recognition system.

Keywords: Offline signature recognition; Modular Neural Networks; Fuzzy integration

1. Introduction

Developing biometric recognition systems for security and identity verification purposes is very active area of research nowadays [1]. Such systems are usually looking for some human traits for the task of recognition, which include a person's fingerprint, their faces, voices, and also their handwriting traits [1]. Fingerprint and iris offer a very high level of certainty as to a person's identity, while the others are less exact. A large number of other techniques are currently being examined for suitability as identity determinants. These include (but are not limited to) retina, gait (walking style), typing style, body odor, signature, hand geometry, and DNA.

Among all biometric features, the handwritten signatures are one of the most popular and reliable ones. They are also the primary mechanism both for authentication and authorization in legal transactions. So, there are two main areas of research related to this matter including signature verification and signature recognition. A signature verification system determines whether the signature is genuine or forger, while a signature recognition system identifies the owner of the signature [2], [3].

There are two main methods for signature verification including on-line approaches and off-line ones. In on-line methods, the sequential data such as handwriting and pen pressure is measured with a special device, while in off-line methods an optical scanner is used to obtain handwriting data written on paper [2]-[4]. The features that are extracted for off-line signature recognition can be categorized as global or local features. Global features describe the signature as a whole such as signature height, image edges, Hough transform [3] and Curvelet transform [5]. Local features are extracted at stroke and sunstroke [6], gradient and concavity features [7].

In this paper, we present a handwritten signature recognition method by using Modular Neural Networks (MNNs) with a Mamdani fuzzy inference system. We have chosen a MNN because they have proven to be a powerful, robust, and flexible tool, useful in many pattern recognition problems [8], [9]. The proposed

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modular neural network in this work composed of three separate modules each of which gets a specific feature of the signature image as their input which include image edges, Curvelet transform coefficients, and the Hough transform matrix. This neural network will lead to very accurate discrimination of the input data used in our experimental tests and also we have confirmed that this MNN system can solve a difficult biometric recognition problem using a simple set of image features.

This paper is organized as follows. In section 2, we briefly introduce the modular neural networks, in section 3, we explain about the curvelet and Hough transforms that are used in our recognition system and Section 4 presents our proposed method which consists of preprocessing, feature extraction and classification stages. The experimental results are given in section 5 and finally conclusions are gathered in section 6.

2. Modular Neural Networks

An artificial neural network (ANN), usually called neural network (NN), is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation [15].

Artificial neural networks are divided into two main categories including monolithic networks and modular ones. In canonical implementations, most systems employ a monolithic network in order to solve the given task. However, when a system needs to process large amounts of data or when the problem is highly complex, then it is not trivial, and sometimes unfeasible, to establish a good architecture and topology for a single network that can solve the problem. In order to overcome some of the aforementioned shortcomings of monolithic ANNs, many researchers have proposed modular approaches [10]. One of the major benefits of a modular neural network is the ability to reduce a large, unwieldy neural network to smaller, more manageable components. Other benefits of these networks are their efficiency, their lower required training time and their robustness.

MNNs employ a parallel combination of several ANNs, and normally contain two main components: (1) local experts; and (2) an integrating unit. Each module is consists of a single artificial neural network, and each is considered to be an expert in a specific task. The outputs of these modules are then combined with each other in some way after the input is given to them. The simplest form of integration is given by a gating network, which basically switches between the outputs of the different modules based on simple criteria, such as the maximum level of activation. However, a better combination of the response from each module can be obtained using more elaborate methods of integration, such as the Mamdani fuzzy inference system.

3. Curvelet and Hough Transforms

Curvelets are a non-adaptive technique for multi-scale object representation. Being an extension of the wavelet concept, they are becoming popular in similar fields, namely in image processing and scientific computing [15]. Curvelets are an appropriate basis for representing images (or other functions) that are smooth apart from singularities along smooth curves, where the curves have bounded curvature, i.e. where objects in the image have a minimum length scale. This property holds for cartoons, geometrical diagrams, and text. As one zooms in on such images, the edges they contain appear increasingly straight. Curvelets take advantage of this property, by defining the higher resolution curvelets to be skinnier the lower resolution curvelets. However, natural images (photographs) do not have this property; they have detail at every scale.

The Hough transform is a feature extraction technique used in image analysis, computer vision, and digital image processing. The purpose of the technique is to find imperfect instances of objects within a certain class of shapes by a voting procedure. This voting procedure is carried out in a parameter space, from which object candidates are obtained as local maxima in a so-called accumulator space that is explicitly constructed by the algorithm for computing the Hough transform [15].

The classical Hough transform was concerned with the identification of lines in the image, but later the Hough transform has been extended to identifying positions of arbitrary shapes, most commonly circles or ellipses.

In automated analysis of digital images, a sub problem often arises of detecting simple shapes, such as straight lines, circles or ellipses. In many cases an edge detector can be used as a pre-processing stage to obtain image points or image pixels that are on the desired curve in the image space. Due to imperfections in either the image data or the edge detector, however, there may be missing points or pixels on the desired curves as well as spatial deviations between the ideal line/circle/ellipse and the noisy edge points as they are obtained from the edge detector. For these reasons, it is often non-trivial to group the extracted edge features to an appropriate set of lines, circles or ellipses. The purpose of the Hough transform is to address this problem by making it possible to perform groupings of edge points into object candidates by performing an explicit voting procedure over a set of parameterized image objects.

4. Problem Statement and the Proposed Method

The problem we address in this paper is concerned with the automatic recognition of a person's signature that is captured on a paper of size 460*792. We have collected a set of signatures from 30 different people which have unique personal signatures. Each person is asked to sign 9 different samples on the paper. Then, these papers are scanned with a KONICA MINOLTA (bizhub C253) scanner to make our data set. Hence, a total number of 270 images are collected for our studies. The system is trained with 7 samples of each person's signatures and then it is tested by the remaining ones. It means that a total number of 210 images are used for training and a number of 60 images for testing.

A new offline signature recognition system is proposed in this paper which consists of an MNN with three separate modules. Our system involves three stages: preprocessing, feature extraction, and classification. All of the images are first cleared from noise and artifacts with some preprocessing methods which are discussed in more details in its specific section. Next, each module is given as input the features extracted with different feature extraction methods: edge detection, curvelet transform, and Hough transform. The outputs of these modules are then combined with each other using a Mamdani fuzzy inference system which determines the person to whom the input signature corresponds. A general schematic of this architecture is shown in Fig. 1, where all the details are clearly shown.
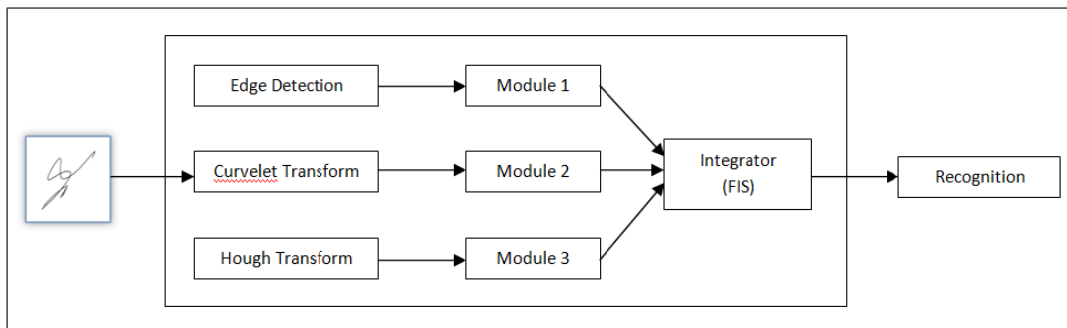

Fig. 1: General Architecture of the proposed Modular Neural Network for signature recognition

4.1. Preprocessing

The preprocessing stage is applied to all scanned images to remove the unwanted noises or artifacts. The size of original signature images is 460*792. First of all, the images are converted from RGB space to gray scale. Next, we obtain the regions of interest (ROI) for each image according to colors. The output of this process will also be a binary image. After that we have created a predefined 2-D filter, we apply it to all images. Finally, we select the regions of interest from all signature images. This technique is based on segmentation that can select desired section of images and therefore the result will be a data base which is free of noises and other unwanted data. At the final step, we resize each image to 20% of its original size. This process is done for decreasing the amount of data which will be delivered to each neural network in future.

4.2. Feature Extraction

In this work, we employ three individual modules, and each receives different image features extracted from the original image of a person's signature. Each of these feature extraction methods are briefly described next.

4.2.1. Edge Detection

For images of handwritten signatures, the edges can capture much of the overall structure present within, because people normally write using a single color on a white background. Therefore, we have chosen to apply Canny edge detector to each image that generates a binary image of edge pixels, see Fig. 2. In this figure we can observe and appreciate the process of edge detection as applied to a particular signature in the database. The Canny algorithm is adaptable to various environments. Its parameters allow it to be tailored to recognition of edges of differing characteristics depending on the particular requirements of a given implementation.
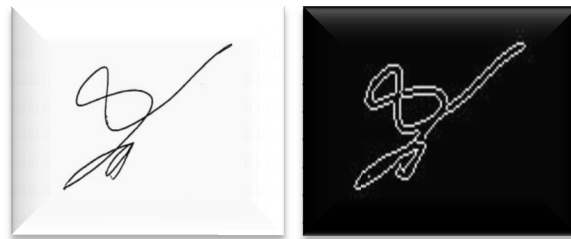

Fig. 2: (a) Original image of signature (b) Image edges

4.2.2. Curvelet Transform

Candès and Donoho introduced multiresolution transform, curvelet, that can capture the intrinsic geometrical structures such as smooth contours in natural images [5]. Curvelets can represent a smooth contour with fewer coefficients compared with wavelets proposed in [11]. The curvelet transform is implemented by decomposing the image into a series of disjoint scales. Each scale is then analyzed by means of a local ridgelet transform. Therefore, curvelet transform is based on multiscale ridgelet transform combined with a spatial bandpass filtering operation at different scales [12]-[14].

4.2.3. Hough Transform

In the third and final module we employ the Hough transform matrix as our image features. This transform can extract line segments from the image. After obtaining a transformation matrix from the original images, another procedure is applied to this produced matrix to extract the peaks of the signature images. This process depends on an important parameter "*threshold*", which is set to its best possible value after conducting some experiments. The original signature image and its Hough transform are demonstrated in Fig. 3.
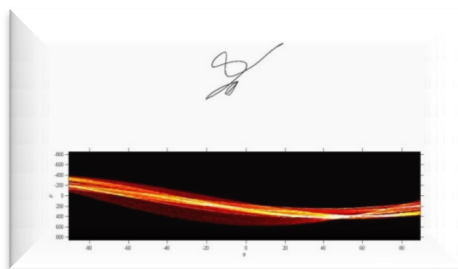

Fig. 3: The Original image of signature and its Hough transform

4.3. Classification

When the outputs of each module is obtained in the modular neural network architecture, the final decision which determines the class of each input signature image should be made by the *Mamdani fuzzy inference system*. Based on our several experiments, the curvelet feature has the highest power in classification of signatures. So, when we have three different outputs from edge detection, curvelet transform and Hough transform modules we trust on what is stated by curvelet feature module.

One of the main stages in designing the fuzzy inference system is determining membership functions for each of our three modules. For this purpose, we have considered 9 membership functions for each of our three features, which are a total of 27 fuzzy rules. Furthermore, the general architecture of the proposed modular neural network with Mamdani fuzzy inference system is demonstrated in Fig. 4.

5. Experimental Results

We divide our experiments into two separate tests in order to show the performance of our proposed method for the problem of signature recognition:

- First, we use each module as a monolithic ANN for signature recognition. Thus, we obtain three sets of results, one for each module, where in each case a different feature extraction method is used.
- Second, we apply our MNN using all three modules simultaneously and the Mamdani fuzzy integral as our integration method.

In all tests 210 images were chosen randomly and used for training, and 60 images were used as a testing set. Furthermore, after some preliminary runs it was determined that the best performance was achieved when the ANNs of the modular architecture are all trained with the Scaled Conjugate Gradient (Trainscg) algorithm, with a goal error of $1e - 006$. Moreover, all networks had the same ANN architecture with two hidden layers. In what follows, we present a detailed account of each of these experimental tests.

5.1. Monolithic ANNs

The best results for the first, second and the third monolithic ANN are summarized in TABLE I. The table shows a feature type which identifies the feature which is used for the signature recognition task, the total epochs required to achieve the goal error, the neurons in each hidden layer, and the total time required for training. Recognition performance is demonstrated with the number of correct recognitions with the 60 testing images, and the corresponding accuracy score.
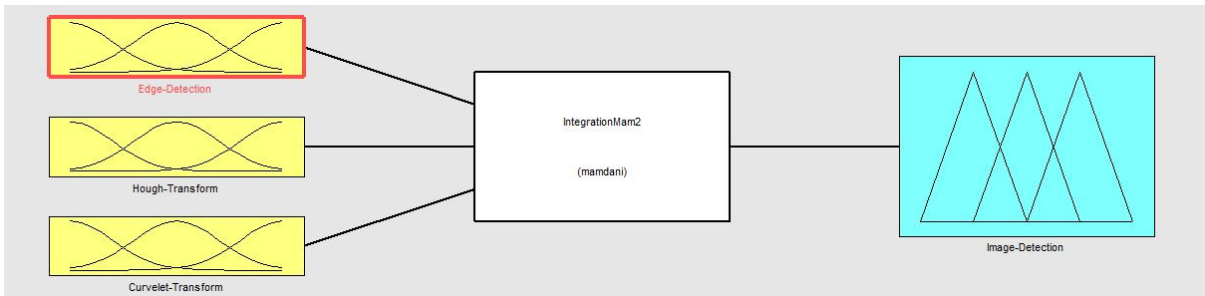

Fig. 4: General Architecture of the proposed MNN with Mamdani fuzzy inference system

TABLE I THE BEST RESULTS OBTAINED FOR MONOLITHIC ANNs VS. OUR MODULAR NEURAL NETWORK

Feature Type	Epochs	Neurons	Time	Correct	Accuracy (%)
edge detection	142	100-80	00:00:44	50/60	83.3
curvelet transform	137	100-80	00:00:10	56/60	93.3
Hough transform	139	100-80	00:01:50	54/60	90
modular neural network	-	-	-	58/60	96.6

5.2. Modular Neural Network with Mamdani Fuzzy Integral

The experimental results in this section correspond to the complete MNN described in Fig. 1, and TABLE I shows the best result obtained from applying the proposed modular system on the test images. Furthermore, the accuracy of our approach can be seen in Fig. 5.
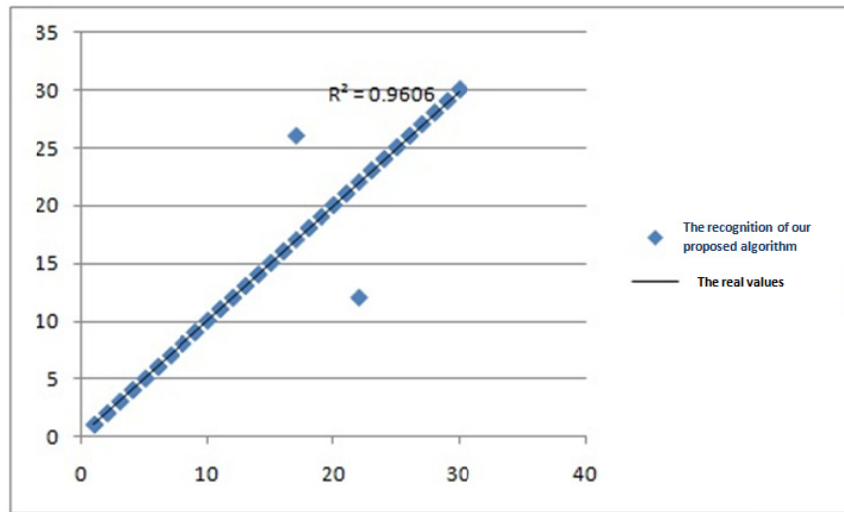
Fig. 5. The accuracy of estimations

6. Conclusions

In this paper, we proposed a modular system using ANNs and three types of image features: edges, curvelet transform, and the Hough transform. In this system, the responses from each module are combined using a Mamdani fuzzy integral. This kind of architecture is referred to as ensemble learning, which is a new paradigm in machine learning topics. In order to test our system, we built a data base of image signatures from 30 different individuals. Our experiments demonstrated that the proposed architecture can achieve a very high recognition rate although the training set is not a big one and thus the results confirm the usefulness of our proposed architecture.

In our tests, we have confirmed that the modular approach always outperforms, with varying degrees, the monolithic ANNs. Furthermore, we believe that if the recognition problem is made more difficult, the modular architecture will more clearly show a better overall performance than the monolithic ANNs.

Moreover, our results also show that even with the nearly simple image features used in this work, each of the ANN modules is indeed capable of learning very good discriminating functions that can correctly differentiate between our set of image signatures.

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